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ORIGINAL PAPER

# Assessing the impact of geo-targeted warning messages on residents' evacuation decisions before a hurricane using agent-based modeling

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**Abstract**
The increasing frequency and intensity of hurricane hazards have raised the urgency of improving hurricane warning effectiveness, especially in terms of motivating the evacuation of people living in high-risk areas. Traditional warnings for hurricanes have limitations of sending a general message for coarse spatial scales (e.g., county level) and do not include specific risks and orders for residents in distinct areas of finer scales. To overcome these limitations, geo-targeted hurricane warning systems have been proposed, but in practice, the existing systems have low accuracy because they neglect environmental factors when defining warning zones. Extant literature has focused on optimizing the geo-delivering process of warnings with limited efforts on geo-defining warning zones. It is still unclear to what extent the geo-targeted warnings motivate residents to evacuate from high-risk areas before a hurricane. Therefore, we developed an agent-based model (ABM) to simulate residents' evacuation decision-making under geo-targeted warnings, which were generated based on characteristics of both hurricane hazards and the built environment. We used forecasted information of Hurricane Dorian as a case study; then conducted the ABMs under geo-targeted warnings, a general warning, and warnings based on storm surge planning zones; then we compared the three outcomes. The research finds an effective way to geo-define warning zones using the built environment data. The result suggests that geo-targeted warnings can motivate more residents in high-risk areas to evacuate. These findings contribute to the understanding of the effect of geo-targeted warning on evacuation and suggest the importance of warnings with more specific contents for finer spatial scales.

**Keywords** Agent-based modeling · Decision-making · Evacuation · Geo-targeted warning · Hurricane

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## 1 Introduction

Climate change has led to the increasing frequency of tropical cyclones worldwide (Rovere et al. 2017). As one of the most frequent and high-impact disasters in the United States (Hao and Wang 2020), recent hurricanes have caused severe social and economic damage to coastal areas (Hasan et al. 2011), including billions of dollars of property damage and the death of hundreds of residents (National Hurricane Center 2020a, b). Particularly, the increasing population made coastal urban areas much more vulnerable to hurricane events (Yao and Wang 2020). Increasing hurricane hazards and coastal population heightened the importance of evacuation during hurricane events. To enhance the residents' compliance with evacuation orders, it is critical to improving the quality of communication (Reynolds and Seeger 2005). When warnings and evacuation orders are issued, timely communication about the projected hurricane trajectory and other attributes (e.g., hurricane categories, wind speed, moving speed) can help residents correctly perceive the risk and motivate evacuation in high-risk regions (Villegas et al. 2013).

Warnings before hurricanes (e.g., warning messages of hurricanes and storm surges) are critical factors that impact individuals' evacuation decision-making (Huang et al. 2016). However, the warnings' influence on mitigating hurricane damages has been underutilized due to the limitations of traditional warning messages: sending a general message for coarse spatial scales (e.g., county level) and not always reflecting the actual risks that residents face (Federal Communications Commission 2020; Gonzales et al. 2016). The same warning for residents across a coarse spatial scale can only reflect the general disaster impact in a relatively large area (Federal Communications Commission 2020). Additionally, traditional warnings were generated mainly based on weather information (e.g., projected hurricane trajectories, categories of hurricanes, wind speed), while the pre-existing spatial characteristics at fine spatial scales, such as land use and topographical characteristics of the local built environment, were not considered in defining warning zones. The limitations of the current warning systems can affect the effectiveness of risk communication before and during hurricanes as residents' perceptions of risk and their evacuation decisions can be influenced by the specificity and timeliness of disaster warnings.

Recently, technologies have been developed to make warnings ***geo-targeted*** (Wood 2018), which can specify warning areas at a county scale (i.e., geo-defining warning zones), and then precisely deliver distinct warning messages to people based on their locations (i.e., geo-delivering warning messages), specifically, distributing the residents to several cellular towers or telephone subscribers when sending warnings (National Research Council 2013; Parker et al. 2015). Because of the wide adaptation of mobile devices (such as smartphones and smart tablets) and mobile Internet, individuals' fine-scale locations are easier to be retrieved compared to the past (Bhattacharya et al. 2020). Based on the fine-scale location, the disaster management departments can design and convey warnings which included the actual hurricane risks faced by the individuals. For example, disaster management departments can transmit messages to cellular phones, radio, television, and NOAA weather radios (National Research Council 2013). Geo-targeted warnings serve as a critical warning strategy in which alerts are transmitted to the residents who are in high-risk disaster-affected regions (NAS 2018).

However, the limited studies and practices related to geo-targeted warnings neglect nuanced environmental factors in the geo-defining process. In practice, wireless emergency alerts (WEA) can provide geo-targeted alerts about imminent threats to safety in the residents' living areas (Wood 2018), but current WEA-generated warnings do not specify distinct risks for residents living in differing areas at fine spatial scales. WEA is a public safety system that sends residents who own compatible mobile devices the geo-targeted, text-like messages, which alert residents to the risks to safety in their area (Federal Communications Commission 2020). WEA generates the warning zones mainly based on the projected hurricane trajectory and strength, and the warning messages reflect this information along with the level of threat and evacuation orders at the county level. Environmental factors, such as land use and elevation, are critical determinants of the hurricane's impact but have been omitted from the WEA's models of expected hurricane impact. Though existing literature has focused on the process of geo-delivering the warning messages and defining the warning areas based on the expected impact of the hurricane (Parker et al. 2015; Wood 2018), not many studies have examined the geo-defining process for geo-targeted warnings. None have predicted or evaluated the influence of the geo-targeted warnings at fine spatial scales on motivating evacuations in high-risk areas. The limited use of more detailed information about a hurricane's impact on a specific area by the WEA and insufficient research mutually prevent further understanding of the effectiveness of geo-targeted warnings and their applications.

Existing studies of warnings for hurricanes have focused on the content and style of warning messages when discussing the impact of warning messages of hurricanes on residents' evacuation decision-making (Lindell et al. 2005; Hasan et al. 2011; Villegas et al. 2013; Huang et al. 2016). These studies mainly used surveys to collect the residents' evacuation decisions in the disaster-affected area. However, the survey participants only experienced receiving warnings from the current warning systems (e.g., WEA). Consequently, survey outcomes cannot reflect individuals' potential responses to improved geo-targeted warnings, which would consider the built environment and apply to a small forecast scale. Therefore, we propose to use agent-based modeling (ABM) to investigate two research questions:

*RQ#1*: How can the environmental factors of the disaster-affected areas be considered in geo-defining the warning zones and designing the warning messages?

*RQ#2*: To what extent can geo-targeted warnings at fine spatial scales (e.g., census tracts) motivate high-risk residents to evacuate?

We utilized the previous empirical findings on the relationship between warnings and residents' evacuation decision-making to simulate the impact of geo-targeted warnings on resident-level evacuation before a hurricane. We specifically simulated the evacuation decision-making under a geo-targeted warning scenario in Miami-Dade County, Florida, in the face of Hurricane Dorian. First, we geo-defined the warning zones based on the physical characteristics of the built environment, e.g., land-use and potential risk of flooding caused by the storm. We also accounted for projected hurricane data, e.g., wind speed and movement routes. Residents in distinct geo-defined warning zones then received targeted warning messages. Next, we generated the evacuation decisions of residents based on the Belief–Desire–Intention (BDI) theory under geo-targeted warnings. BDI modeled decision-makings by considering perceived information, previous decisions, and the demographics of decision-makers to generate the predicted preference for possible decision options. To assess the effectiveness of geo-targeted warnings on motivating residents to make evacuation decisions, we compared simulation outcomes of residents' evacuation decisions under three scenarios: geo-targeted warnings, general warnings, and the warnings based on storm surge planning. The results showed that geo-targeted warnings can motivate residents in the study area to evacuate more effectively, especially for residents living in high-risk areas.

## 2 Literature review

### 2.1 Existing warning systems and warning messages of hurricanes in the U.S.

U.S. residents mainly receive authoritative warnings about emergencies and disaster hazards from the following warning systems: the WEA service, the Emergency Alert System (EAS), and the National Oceanic and Atmospheric Administration's (NOAA) Weather Radio (NWR). These systems have been combined into the Integrated Public Alert and Warning System (IPAWS), which is administrated by the Federal Emergency Management Agency (FEMA) (Wood 2018). They can provide geo-targeted emergency warnings to users in the disaster-affected areas. However, both geo-defining and geo-delivering steps have been inaccurate in the current system (Wood 2018). The smallest warning scale is at the county scale but risk levels within a county can be extremely diverse during hurricanes (FCC 2020). Hurricane information was still a major factor in defining warning areas and environmental information was not considered when generating the warnings.

In addition to the accuracy of the geo-defining and geo-delivering, other elements of hurricane warning messages influence their effectiveness, such as the content, sources, and transmission channels of the warnings (Morss et al. 2016; Bui 2019). Warning messages of hurricanes usually consist of basic information about the event and possible influences on people's personal lives (Wei et al. 2014). The design of warning messages should also reflect the features of specific hurricanes, e.g., location and time of landfall, hurricane category, wind duration, general track of the hurricane (Villegas et al. 2013), and predicted impact on the built environment: e.g., house inundation, house damage caused by storm winds, injury, job disruption, and service disruption (Wei et al. 2014). Wang et al. (2020) discussed the importance of including characteristics of the hazard, such as the guidance for responses, location, duration and period of the incoming hurricane, and the source of the warning messages.

Limitations exist in the current warning system and in previous research of warning messages before hurricanes, which were related to the warning content and the dissemination process. In current warning messages, the description and prediction of hurricane characteristics are determined by projected information of the hurricanes, but the estimated influences on personal life depend on individual living places. For example, inundation is associated with both storm intensity and the topography of the affected areas. However, environmental aspects of living places are generally ignored in the warning messages, and the precision of warning messages is accordingly reduced. To comprehensively address the personal risk of hurricanes, geo-targeted warnings should be finer-gained, and warning zones should be defined based on both projected hurricane attributes and the environmental situation of the affected areas. Research into the dissemination of warning messages has also been insufficient. Particularly for geo-targeted warnings, there has been insufficient discussion of the geo-defining of warning zones. Previous research has mainly focused on the precision and performance of the geo-delivering of warning messages (Parker et al. 2015; Gonzales et al. 2016); the precision of geo-delivering includes, for instance, the proportions of the population who should receive and who do receive the messages. By contrast, the geo-defining of warning zones largely lacks discussion, and the question of whether geo-targeted warnings can motivate residents to evacuate has yet to be examined. Therefore, considering the limitations of current warning systems and related research on geo-targeted warning, there is an urgency of including the environmental information in the design of warning messages and to further discuss the influence of geo-defining of warning zones on human behavior in hurricane responses.

### 2.2 Influence of hurricanes risk communication and warnings on residents' behaviors

To determine whether geo-targeted warnings can motivate evacuation, it is critical to analyze the influence of warnings before hurricanes on residents' behaviors, such as motivating or hindering evacuation (Sutton and Kuligowski 2019). We reviewed the literature on risk communication and warnings to gain comprehensive knowledge, as these activities have similar purposes both before and during adverse events (e.g., mitigating the impacts of disasters). Risk communication is the process by which individuals, groups, and institutions exchange information and opinions (National Research Council 1989) and is an important research field in disaster management. Effective risk communication informs the public so they can make life-saving decisions (Reynolds and Seeger 2005). For example, residents in flood-affected areas who take protective measures after receiving risk messages can reduce monetary damages by 80% (Grothmann and Reusswig 2006). The literature discusses a variety of factors in residents' behaviors after receiving risk information about disasters (Eiser et al. 2012; Huang et al. 2016), such as the influence of previous experiences on risk judgment and the trustworthiness of different information sources (Halpern-Felsher et al. 2001; Eiser et al. 2012). Comparing to risk communication, warnings contain risk information about hurricanes and are published by authorities (e.g., National Hurricane Center) to inform residents in disaster-affected areas (Anthony et al. 2014). Because of the severe damage caused by hurricanes, it is important that these warnings timely lead residents of high-risk areas to take protective measures, such as evacuation, before hurricanes.

Research has indicated that evacuation decisions following warnings are affected by many factors: environmental factors (e.g., the status of living places) (Hasan et al. 2011), the surrounding built environment (Sun et al. 2014), storm factors (Baker 1991), personal factors (e.g., demographic characteristics) (Goodie et al. 2019), hurricane experience (Hasan et al. 2011), family relationships (Nejat et al. 2016), and information (e.g., news and warning messages) (Onggo et al. 2014). However, information factors are the only ones that can be controlled by disaster managers in the short term. These factors, in individuals' evacuation decisions, include the information's source and the descriptions of the event (Huang, et al. 2017). They affect people's perception of and response to warnings. If the information is accurate and reflects the actual risk level of the residents, residents can make rational decisions to take protective measures. However, because environmental information is neglected, previous warnings before hurricanes have been unable to accurately describe the risks faced by residents. In addition, the discussion of geo-defining warning zones and the influence of geo-targeted warnings on residents' evacuation decisions has been insufficient.

### 2.3 Analyzing and modeling disaster warnings' impacts on evacuation

An array of studies has investigated the behaviors affected by disaster risk communications and warnings, including empirical studies (Haghani and Sarvi 2018) and behavior simulations (Jumadi et al. 2017). The empirical studies focused on observing crowd responses (e.g., evacuation, information seeking). However, these studies were criticized for several drawbacks, such as lack of observation data, inability to analyze variation in individuals' behavior patterns, and inconsistencies in the environmental information of residents in different studies (Haghani and Sarvi 2018). The complexity of individual behavior also makes it difficult to characterize or measure in surveys. Although some researchers used video records of disasters to observe and define behavior patterns (Bernardini et al. 2016), such records were not always available, and the status of residents cannot be determined from short videos, which limited the potential for further analysis.

Different from empirical studies which focused on measuring the different factors in residents' evacuation behaviors, simulation research has focused on defining the behavior patterns of residents and simulating their evacuations under different scenarios. Jumadi et al. (2017) summarized the methods used for disaster behavior simulation, such as ABM and linear programming. ABM is the most used method because of its ability to accommodate system complexity and analyze agent-environment relationships. This is especially useful for studies of disasters' large-scale impacts on the population. ABM has been used to simulate details of numerous disaster scenarios, such as individual risk estimation for flood events in Towyn, U. K. (Dawson et al. 2011), warehouse evacuation for fire (Joo et al. 2013), hurricane evacuation in New Orleans (Liang et al. 2015), evacuees' movements in videotapes of earthquake events worldwide (Bernardini et al. 2016), and tsunami evacuation in Iquique, Chile (Leon and March 2016). In these studies, evacuees were abstracted to agents, and their decisions and movements were simulated by pre-designed mechanisms or rules (e.g., pedestrian walking patterns in outdoor spaces, traffic rules on the urban roads).

However, the main objective of these studies was to simulate the evacuation movement of residents in areas affected by specific disasters, for instance, to identify vulnerable areas at the urban or community scale and propose strategies for improving disaster resilience. Few have simulated the people's aggregated evacuation decisions at large spatial scales (e.g., cities or counties). This is because, whereas transportation was simply determined by traffic regulations, individual evacuation decisions at the urban scale are very complex and depend on many factors (e.g., warning information received, demographic characteristics). Current research into warning and evacuation simulation has a gap regarding the influence of warning information on residents' evacuation decisions; namely, it is necessary to integrate the influences of internal and external factors on these decisions and then simulate and compare the effects of different types of warning information. Therefore, we propose to examine the influence of geo-targeted warning messages that considers environmental information about people's residences on their evacuation decisions. The ABM method was used to model residents' decisions and reveal the influence of warning information on motivating evacuation decision-making.

## 3 Methodology

To answer the research questions, we developed geo-targeted warning scenarios and simulated residents' evacuation decision-making. This method is consisted of two major procedures: (i) data and simulation framework preparation and ii) warning scenario development and evacuation decision-making simulation process (see Fig. 1). The data and framework preparation included identifying the entities in the simulation process and their relationships, and then collecting data for them (e.g., demographic data for the residents). After preparing the data and simulation framework, we geo-defined different warning zones and

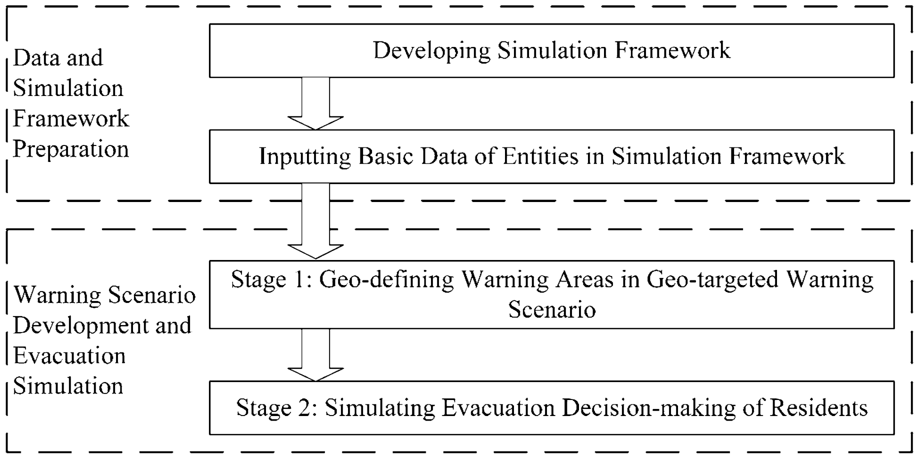


**Fig. 1** Research procedures

simulated the decision-making of evacuation at the individual level for residents in the studied area.

Several *assumptions* have been made to develop the ABM. (i) The residents make decisions independently based on their demographic characteristics and received warnings. (ii) All residents living in the study area has experienced a hurricane before. (iii) The decision-making process of a resident will stop if they decide to evacuate.

### 3.1 Constructing ABM entities and relationship

The basic structure of the ABM included a set of agents, agent relationships, and the related environment. ABM was particularly useful for predicting aggregated human behaviors in disasters because individuals' behaviors were difficult to be mathematically approximated, but the individuals' behaviors can be determined by the rules of movement and decision-making, and a series of simple relationships between individuals and other entities. Additionally, compared to empirical studies of human behaviors in disasters, ABM can model aggregated decision makings of individuals' behavior at large population scale.

The running of ABM was essential to have agents (i.e., individuals) to repeatedly execute their behaviors and interactions (Bonabeau 2020). Based on the modeling process in previous studies (Liang et al. 2015; Leon and March 2016), our ABM includes two types of entities: human agents and environmental zoning. The human agents represent the population who live in the study area during the study period. The environmental zoning describes the conditions of the built environment and hurricane conditions, including land use conditions, flooding zoning, and the wind speed and distance of the hurricane event. We also assigned values for different attributes of the entities. Specifically, human agents were characterized by age, gender, income, education level, housing type, and household types. Environmental zoning is featured by land use conditions and types of flooding zoning at census tract scale. Relationships of the entities were built in ways that the built environment and hurricane information were utilized to form the warning scenarios, and the agents' demographic characteristics and the warning information they received were the basements of agents' evacuation decisions. We then collected data for different entities and

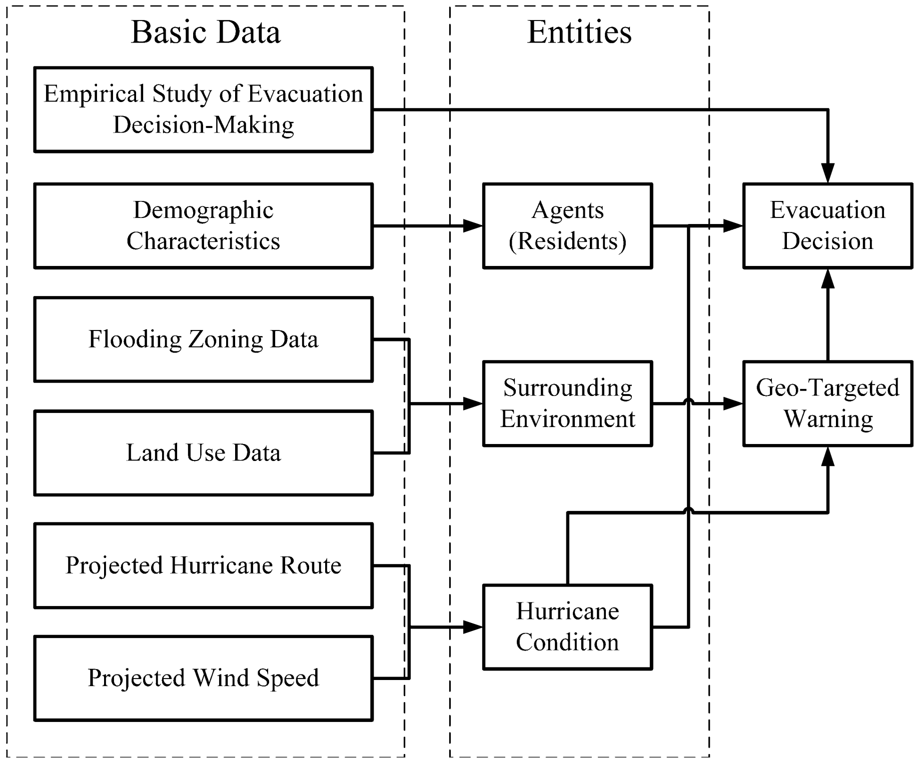


**Fig. 2** Structure and components of the ABM Platform

their relationships, including residents' demographic data, land use data, flooding zoning data, and projected hurricane route and wind speed. We also utilized findings from previous empirical studies (Hasan et al. 2011; Huang et al. 2016) about how different factors affecting the evacuation decision of residents during hurricanes (Fig. 2).

## 3.2 Warning scenario development and evacuation simulation

### 3.2.1 Geo-Defining warning zones for projected hurricane-affected areas under geo-targeted warnings

In this research, we focused on the geo-defining process and defined the geo-targeted warning zone as the regions which were: (1) located in high-risk flooding zones based on flooding zoning, (2) located in a high-density residential area, and (3) close to the projected hurricane-influenced area. To geo-define warning zones, we first calculated the risk level of each census tract in face of hurricanes based on the types of land use and flooding zoning. The study focuses on residential land use as high population density leads to high risk (Bakkensen and Mendelsohn 2016). For the flooding zoning data, elevation and the type of flooding zone were also considered: a high elevation degree and a high level of potential inundation depth can lead to a high level of hurricane risk (Rey et al. 2019). After calculating the level of risk to hurricanes, we determined the geo-targeted warning zones based on both vulnerabilities of the census tracts (which were related to the flooding risk) and the wind speed. If the census tracts are with a high level of hurricane risk and close to the high-speed wind influence area (we set the distance as 200 miles, which indicates that hurricanes with the speed of 74 mph may arrive in less than three hours), they were aggregated as the warning zone that received geo-targeted warning messages. The calculation method of risk level for the geo-targeted warning is shown as Eq. 1 and 2. In Eq. 1, "Risk" is the census tract-level disaster risk under the current hurricane events, "*Norm*()" is the processing method to normalize the indicators' value, "WS," "FZ," and "LU" are the risk value of wind speed, flooding zoning, land use in the related census tract. We generated the normalized values of these indicators by dividing the actual values by the maximum value of the indicators. For example, if the maximum risk level of FZ is "6," the census tracts that have the "FZ" value in "3" would be assigned with normalized "FZ" value as "0.5." For the categorical factors, i.e., "FZ" and "LU," the risk levels of different categories were assigned with numerical values that ranged from 0 to 1. For example, the risk of "vacant" land-use would be assigned with "0," and the risk of high-density residential zones would be assigned with "1." The normalization process of indicator values made them comparable in the same equations. Because the projected hurricane attributes change dynamically, we calculate the risk level based on each record of the hurricane attributes, shown as $Risk_i$, which is the risk level of the census tract based on the *ith* record of the hurricane.

$$\text{Risk}_i = \frac{(\text{Norm(WS)} + \text{Norm(FZ)} + \text{Norm(LU)})}{3} \times \text{Hurricane Distance} \tag{1}$$

$$\text{Hurricane Distance} = \begin{cases} 0, \text{if the distance is larger than 200 miles} \\ 1, \text{if the distance is less than 200 miles} \end{cases} \tag{2}$$

After generating the geo-targeted and general warnings in the level of the census tracts, we assigned the warning messages to the human agents. Specifically, in each time point, based on the located census tracts, human agents were assigned the value of the risk level of hurricane events, which was also one factor of the agents' evacuation decision-making. The values of the risk level were included in each round of the calculation of agents' evacuation decisions, which was described in detail in Sect. 3.2.2.

### 3.2.2 Simulating residents' decision-making of evacuation

After geo-defining the warning areas, we then modeled the decision-making process of evacuation (i.e., evacuate or not) for individual residents. Compared with household-level simulation, resident-level decision-making can be approximated more accurately (Hasan et al. 2011) due to the available empirical findings on the direct relationship between the personal decision-making process and demographic characteristics (Huang et al. 2016) as well as the open-access census tract data (U.S. Census Bureau 2019). This enables simulation at individual-level agents based on demographic data. We defined rules for agents' evacuation decision-making by considering individuals' vulnerability to hurricanes as well as their resided warning zones to determine the probability of evacuation. For example, if the vulnerability of an agent to the hurricanes was 0.5, when this agent received the warning that the risk of the hurricanes (i.e., the abstract level of the negative impact of hurricanes on individuals' life) was extremely high (we assumed that the risk was 1.0 within the scale of 0.0 to 1.0), the agent has the probability of 0.5 to evacuate from the current living place. Based on these rules, residents' evacuation decision was made when the residents received the warning at a certain time point and residents can make decisions over consecutive time points. We employed the belief–desire–intention paradigm (BDI) as the simulation model (Lee et al. 2010) to approximate the decision-making process. BDI is a decision-making model, by which we can simulate the agents' decisions based on the agents' received information, decisions in the last round of the simulation, and the demographic attributes of them. Because we aimed to simulate agents' decisions, we utilized the model of Decision Field Theory (DFT) (Busemeyer and Diederich 2020) as the calculation method of human agents' decisions (i.e., evacuate or stay). The calculation equation of DFT is as follows:

$$P(t+h) = S \times P(t) + C \times M(t+h) \times W(t+h) \tag{3}$$

In Eq. (3), $P(t)$ and $P(t+h)$ are the evacuation decisions, and the agents' initial decision of evacuation is set as "staying"; stability matrix S represents the lingering effect of the preference from the previous state) and the effects of interactions among options; the matrix $M(t)$ (an $m \times n$ matrix, where $m$ is the number of options, and $n$ is the number of attributes) represents the subjective evaluations of an evacuee regarding each attribute of each evacuation decision; The weight vector $W(t)$ (an $n \times 1$ vector, where $n$ is the number of attributes) allocates the weights of attention corresponding to each attribute considered at time $t$. Because different evacuation options are assessed independently, $C$ is an $m \times m$ identity matrix. The subjective evaluation of each evacuation options forms the matrix $M(t)$. Combined with the weight matrix, we can integrate the risk evaluation of different factors based on BNN and generate residents' evaluation of evacuation options (i.e., evacuate now or not). For hurricanes, we simulated residents' decision makings of evacuation based on their vulnerability level and the risk level of the hurricane. The simulation methods of evacuation decisions were applied in all the warning scenarios, such as geo-targeted warnings and general warnings. We adopted the correlation of different demographic characteristics to the residents' evacuation decision-making from previous empirical studies (Huang et al. 2016; Hasan et al. 2011) as the weight of each factor in calculating individuals' vulnerability. These previous studies extracted the correlations' value by conducting surveys among the general U.S. residents, which made the values of correlations reflect the general relationships between U.S. residents' demographic characteristics and their evacuation willingness. Because the human agents generated by these studies (Huang et al. 2016; Hasan et al. 2011) were also reflecting the general demographic characteristics of the local areas, the generalized value of correlation coefficients could be applied to calculate the agents' vulnerability. The risk level changes along with the changing hurricane attribute in each round of simulation. The calculation method of an individual's vulnerability is shown in Eqs. 4 and 5. Based on the calculation process in Eqs. 4 and 5, we can randomly generate residents' decisions about evacuation when receiving the geo-targeted hurricane warning based on each record of the hurricane.

$$\begin{aligned}\text{Vulnerability } &= 0.05622 \times \text{gender} + 0.01755 \times \text{age} + 0.02459 \times \text{education} + 0.00965 \times \text{income} \\ &+ 0.04598 \times \text{housing} + 0.01852 \times \text{household}\end{aligned} \tag{4}$$

$$\mathrm{P}\left(t_{i+1}\right) = S \times P\left(t_i\right) + C \times \text{Vulnerability} \times \text{Risk} \tag{5}$$

For the demographic characteristics, $f_j$(Demographic) ($j$ is from 1 to 6) is the influence of the residents' demographic characteristics on residents' vulnerability to hurricanes. For Eq. 5, we adopted the theory of BDI to generate residents' evacuation decision: $P\left(t_{i+1}\right)$ and $P\left(t_i\right)$ are the evacuation decision of residents based on the warnings they received at time points of $t_{i+1}$ and $t_i$. For $P(t_0)$, we assumed the initial decision is “not to evacuate” because the residents received no warning at that time. Once the residents decided to evacuate, we assumed that their decisions remain to the end of the simulation. The development of agents’ decision was a stochastic process. Specifically, we calculated the value of “C × Vulnerability × Risk” in Eq. 5 as the probability that the agents decided to evacuate in the simulation round. Based on this probability, we set a generator of random outcomes based on this probability. For example, if the value of “C × Vulnerability × Risk” for one agent was 0.6, this agent would decide to evacuate in this round with the probability of 60%.

Lastly, we measured the evacuation decision-makings using the percentage of residents who decided to evacuate in each census tract, and the regional-evacuation outcome was calculated by integrating the evacuation outcomes of all parcels in the whole study area.

## 4 Case study, results, and evaluation

### 4.1 Case description and data collection

We specifically focused on the urban areas of Miami-Dade County in Florida that were affected by Hurricane Dorian (National Hurricane Center 2020a, b), shown in Fig. 3. We studied Miami-Dade County because the frequency and severity of recurrent hurricanes in this area are usually higher than in other urban areas in the U.S. (Chen et al. 2006).

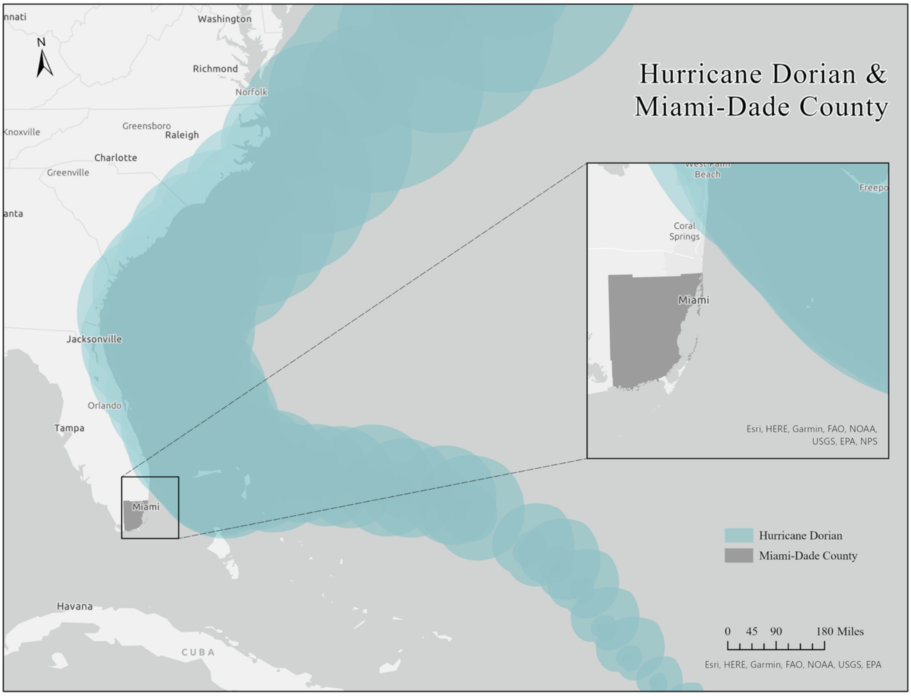


**Fig. 3** The spatial impact of Hurricane Dorian on Miami-Dade County (15:00 EST August 24 to 3:00 EST September 9, 2019)

Residents in this area also have experienced tropical storms or hurricanes before (Bostrom et al. 2018). Additionally, based on the census data and traffic planning, the urban area of Miami-Dade County has several storm-surge planning zones (Miami-Dade County 2020), but limited routes for the residents to evacuate (Sadri et al. 2015). This condition may lead to severe traffic jams if residents rushed to the evacuation routes from areas of all risk levels instead of going to shelter space when exposed to low-level risks (Smith and McCarty 2009). Therefore, it is urgent to have geo-targeted warnings that can help residents to have an accurate perception of the hurricane risks and motivate residents in high-risk areas to evacuate. Also, Hurricane Dorian has different projected trajectories (passing Florida) from the real hurricane trajectory (bypass Florida, North, and South Carolina) and the warnings have triggered large-scale population terrors and overreactions (CNN 2019; NOAA 2019b). Although Hurricane Dorian did not pass Miami-Dade County, the actual condition and projected track of Dorian still had notable effects on residents' evacuation decisions. Therefore, it is still a valuable case for studying the effects of different warning messages. We collected the projected movement path and wind speed data of Hurricane Dorian during the period from 15:00 EST August 24 to 3:00 EST September 9 from NOAA (2019a). Because the National Hurricane Center and Central Pacific Hurricane Center generated the projected hurricane records every six hours, we were able to collect 65 projected hurricane records over our studied period for our ABM under different scenarios. All the simulation outcomes and geo-defined warning zones were shown in Supplementary Materials.

First, we collected basic data to construct entities and their relationships for ABM. The projected hurricane trajectory and affected areas (including the urban area of Miami-Dade County) are shown in Fig. 3. The urban area in Miami-Dade County included 1379 census tracts (U.S. Census Bureau 2019), characterized by distinct social and demographic features. Personal demographic information was not available, so we randomly sampled one percent of the population (i.e., 25,049) based on the demographic attributes of the ABM agents. With this percentage, the agent population in each census tract was determined by the real-world local populations. For example, for the census tract that had one thousand residents, we created ten agents (i.e., 1% of the local population) on this census tract. The demographic characteristics of these agents were randomly determined based on the distributions of demographic conditions of the census tract. For example, if the proportion of male residents in one census tract was 50%, the agents in this block had the probability of 50% to be male agents. The determination of other demographic characteristics was also based on this rule. Based on the percentage of different categories of these demographic characteristics, we can create agents whose demographic characteristics can represent the local population of each census tract. Specifically, categories of the demographic features for simulating agents are listed in Table 1.

For the built environment (Fig. 4), there were 98 types of land use in the study area, including agricultural, transportation, industrial, educational, residential, and recreational land use (University of Florida GeoPlan Center 2019), and we focused on the residential areas because these areas contained most of the population in the study area, and the warning messages of hurricanes aimed to motivate residents to evacuate if their living places have the high-level risk of hurricane disasters. The flooding zoning data recorded the general elevation and types of flooding zoning of each area in Miami-Dade County (Miami-Dade County 2015). Based on the flooding zoning data, the elevation of the study area was from 0.0 m to 18.0 m, and there were seven types of flooding zones, including A (unnumbered high flooding risk), AE (moderate to high flooding risk), AH (moderate to the high flooding risk, less risky than AE), D (areas with possible but undetermined flood hazards), open water, VE (High Flooding Risk) and X (moderate flood hazard areas),

**Table 1** Categories of each demographic characteristics

| Demographic features | Categories |
|---|---|
| Gender | Male; Female |
| Age | Under 5, 5 to 17, 18 to 21, 22 to 29, 30 to 39, 40 to 59, 50 to 64, 65 to 74, 75 to 84, higher than 85 |
| Income | Less than 10,000, 11,000 to 14,000, 15,000 to 19,000, 20,000 to 24,000, 25,000 to 29,000, 30,000 to 34,000, 35,000 to 39,000, 40,000 to 44,000, 45,000 to 49,000, 50,000 to 59,000, 60,000 to 74,000, 75,000 to 99,000, 100,000 to 124,000, 125,000 to 149,000, 159,000 to 199,000, more than 200,000 |
| Household types | Family household; Non-family household |
| Housing types | Owner-occupied housing; Renter occupied housing |
| Educations | Less than 9 years, less than 12 years, some college (less than 1 year), college |

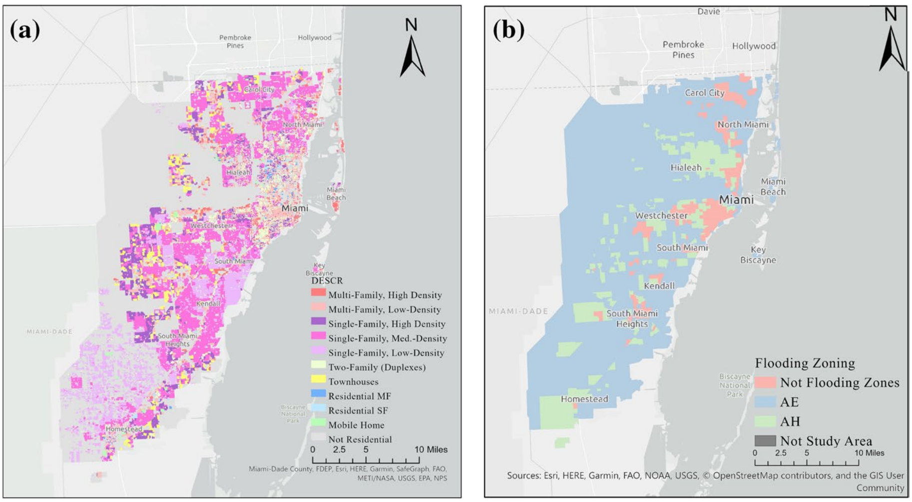


**Fig. 4** Land use and flooding zoning of the study area (**a**: Land Use, **b**: Flooding Zoning)

and the classification of flooding zones was based on the probability of occurring one-percent-annual-chance shallow flooding. The environmental data in the simulation framework were fine-grained, which were in the census-tract level. Using the census-tract-level environmental data, we can develop the geo-targeted warning messages which reflected the actual hurricane risks in small-scale areas, and the warning messages would not be overgeneralized.

### 4.2 Geo-defining targeted warning zones in the study area

We used ten NOAA records of Hurricane Dorian from 3:00 September 2 to 9:00 September 4 as the projected hurricane information and defined our studied residential areas as census tracts within 200 miles of the trajectory center of the hurricane. Then, we calculated the risk level of each census tract based on the wind trajectory and speed and their spatial relationship with the flooding zone (FEMA 2019). If the wind zone of the hurricane did not pass the census tracts, we assumed the wind speed of the tracts was the same as hurricane-influenced areas that were closest to these census tracts. The risk levels of the census tracts were also affected by the land use types, as the regions of the high-density population (e.g., multi-family residential areas) were assigned with a higher level of risk than the regions of the low-density population (e.g., single-family residential areas). If the census tracts were within a high-risk flood hazard area (zone AE, AH, A), they would be assigned a higher level of risk than the areas located in the low-risk flood hazard areas. We also considered the population density of the census tracts, as high population density areas were of higher risks. Based on these factors, we generated different warning zones (e.g., the warning zone identification outcome of 3 am EST on September 2 is shown in Fig. 5). All the geo-defined warning zones are shown in Table 2 of the Supplementary Materials. The areas of red were the warning zones for high-risk census tracts, while the yellow areas were the comparatively low-risk census tracts.

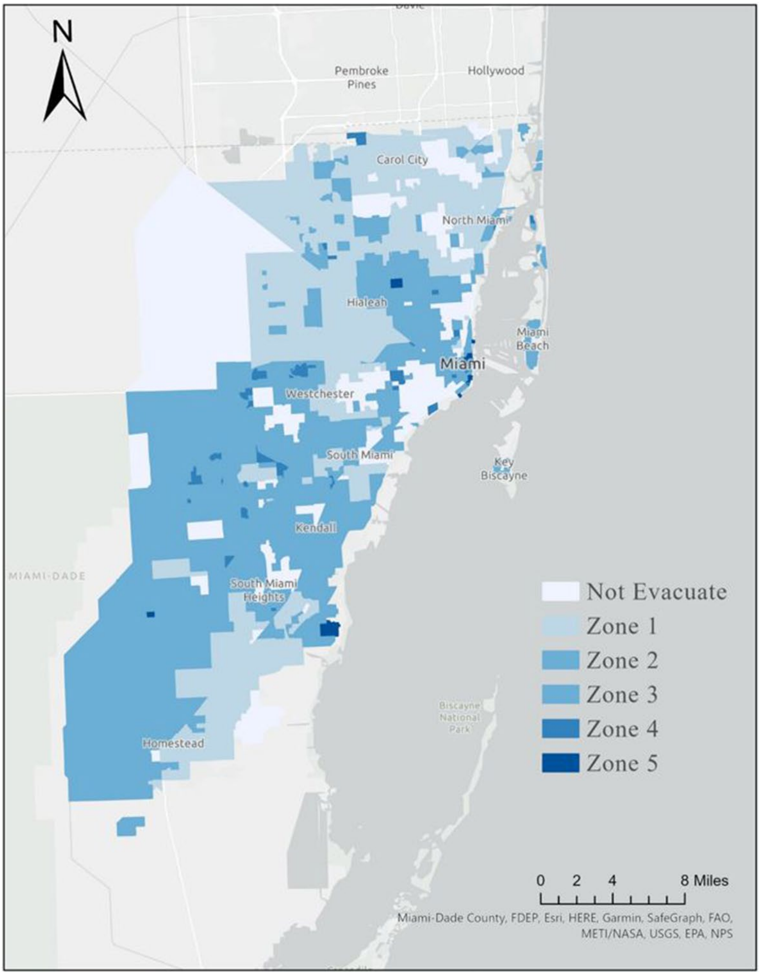


**Fig. 5** The geo-targeted warning in Miami-Dade County at 3:00 A.M. September 3rd

**Table 2** Example warning information

| Warning zones | Relative risk level to the hurricane | Example geo-targeted warning information |
|---|---|---|
| Warning zone 1 | Under 0.2 | The risk of hurricanes in your living area is very low, evacuation is not very necessary |
| Warning zone 2 | From 0.2 to 0.4 | The risk of hurricanes in your living area is low, evacuation is not necessary |
| Warning zone 3 | From 0.4 to 0.6 | The risk of hurricanes in your living area is medium, you can consider evacuating from the current living place |
| Warning zone 4 | From 0.6 to 0.8 | The risk of hurricanes in your living area is high, evacuation is necessary |
| Warning zone 5 | From 0.8 to 1.0 | The risk of hurricanes in your living area is very high, evacuation is very necessary |

Based on the geo-defined zones, residents living in distinct warning zones would receive geo-targeted disaster warnings with localized risk levels and evacuation suggestions. Table 2 shows an example of the warning messages for different zones based on the simulation result of 3:00 A.M. EST on September 2.

### 4.3 Simulating residents' decision-making of evacuation

In this research, residents' evacuation decision-making is based on the warning information and their vulnerability to hurricane events. We evaluated individuals' vulnerability mainly based on their demographic characteristics and socioeconomic status, including gender, age, income level, household type, housing type, and education level. The evacuation outcomes of the last round of the simulation under geo-targeted warning and general

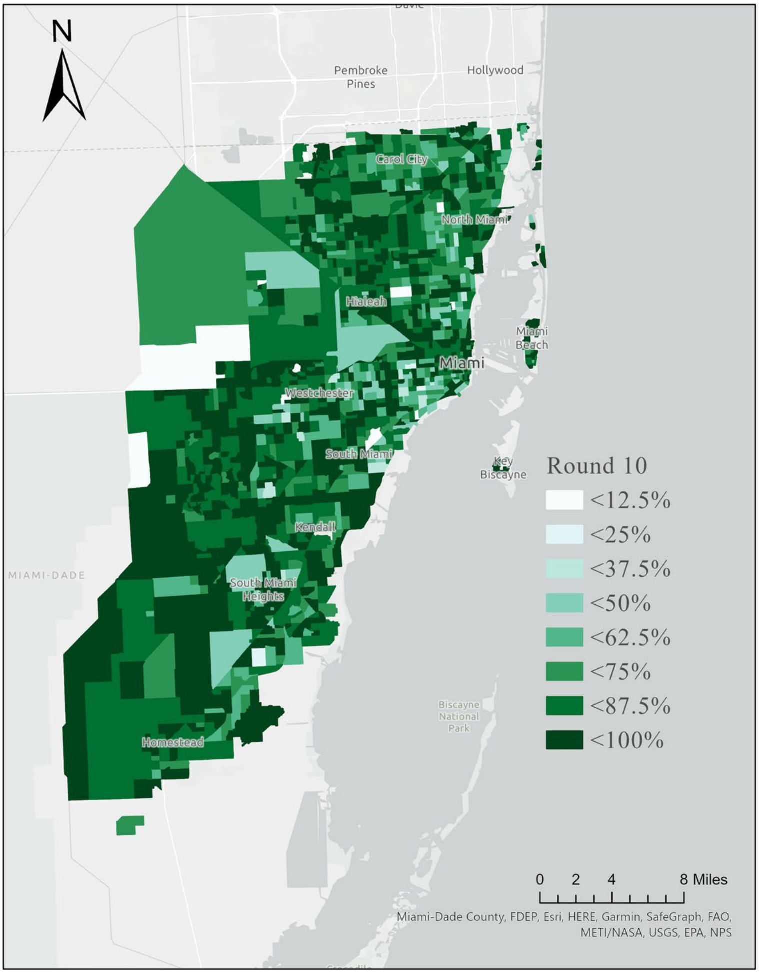


**Fig. 6** The percentage of residents who decide to evacuate under geo-targeted warning across census tracts at 9:00 A.M. EST September 4th

warning are shown in Fig. 6. All the simulation outcomes under the geo-targeted warning scenario are shown in Table 2 of the Supplementary Materials. In this map, the colors of census tracts represent the percentage of residents in each tract who have made the evacuation decisions. Based on the evacuation decision-making, the percentage of people who decide to evacuate varied across census tracts and warning zones, and most of the tracts in high-risk warning zones (such as Zone 3, Zone 4, and Zone 5) have percentages higher than 40%. However, without comparing to other types of warning messages, the simulation outcomes under geo-targeted warnings were not sufficient to assess the motivation effectiveness of geo-targeted warning. Therefore, to evaluate the influence of geo-targeted warnings on motivating residents to evacuate, we simulated the evacuation decision-makings under other warning messages or evacuation planning to evaluate the motivation influence of geo-targeted warnings.

## 5 Evaluation of simulation results

To evaluate the ABM outcome of the geo-targeted warning (see Fig. 6), we conducted the ABM of residents' evacuation decision makings under the general warning scenario (Comparison Scenario 1) and the storm surge planning in Miami-Dade County (Comparison Scenario 2) and compared the three outcomes. The outcomes of the comparison scenarios are shown in Fig. 8, and all the simulation outcomes under the general warning scenario and the warning scenario based on storm surge planning are shown in Tables 3 and 4 of the Supplementary Materials. In Scenario 1, the geographic information of the study area was not considered when geo-defining the warning zones, only "projected" wind speeds of Hurricane Dorian were included in the geo-defining process. If census tracts were close to the high-speed wind influence area (i.e., the distance between hurricane trajectory and the centroid of a census tract is less than 200 miles), the tracts received the same warning messages (i.e., general warning), and the level of hurricane risk was set as 1. In Scenario 2, the Storm Surge Planning Zone categorized areas that could be affected by a storm surge of 1.5 feet or higher during a hurricane. For our studied area, evacuation orders were mainly developed by Miami-Dade County's Emergency Operations Center based on storm surge planning (Miami-Dade County 2020). The Center divided the planning zones into six categories based on the risk for storm surges of different levels. When conducting simulation in Scenario 2, the level of hurricane risks was determined by the pre-identified storm surge risk level in the plan. Storm surge planning zone was an important reference of the official evacuation orders (Miami-Dade County 2020). Despite the value assignment of hurricane risks, other components of the calculation method of agents' evacuation decision-making were the same as that in geo-targeted warning scenarios. The warning zones of both comparison scenarios are shown in Fig. 7.

We also calculated and evaluated the population of residents with evacuation decisions in the high-risk zones of the study area under different warning scenarios, and the high-risk zones are the census tracts that have a risk level higher than 0.5. We found that more residents decided to evacuate from the current living place under geo-targeted warning than the two comparison scenarios. The overall percentages of residents who decide to evacuate under different warning scenarios over the last round of the simulation are shown in Fig. 9. The population of residents who decided to evacuate in the whole area increased rapidly in the first several rounds, and then slowly. We have also assessed the effectiveness of warnings specifically for the high-risk urban areas, which have several storm surge planning

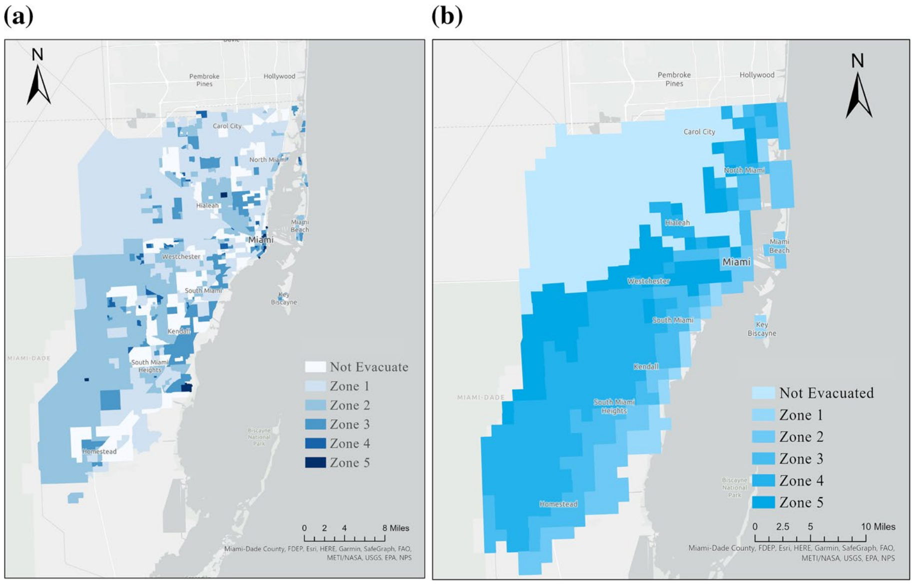


**Fig. 7** The general warning **a** and warning based on storm surge planning **b** in Miami-Dade County at 3:00 A.M. September 3rd

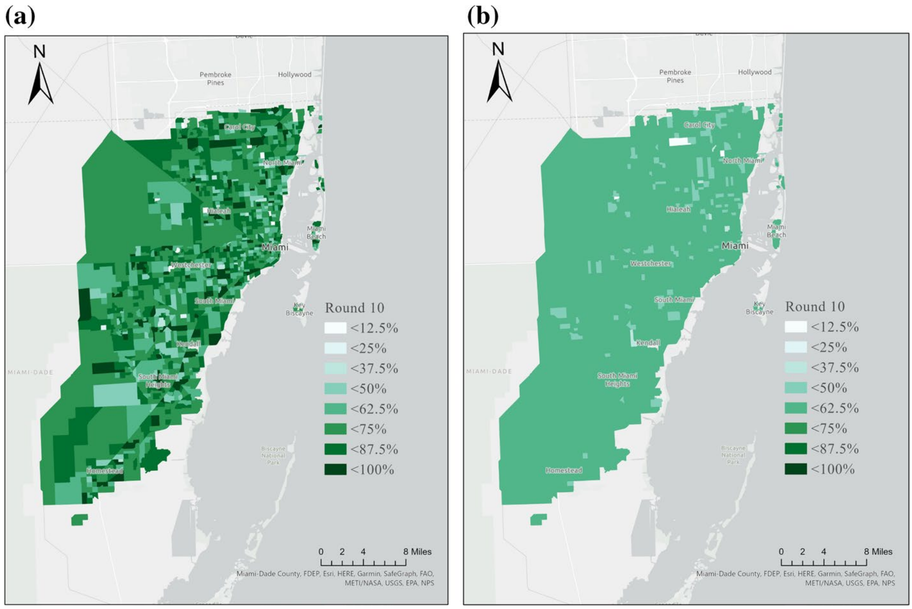


**Fig. 8** The Percentage of residents with evacuation decision based on general warning scenario **a** storm surge planning zones **b** of the study area at 9:00 A.M. EST September 4th

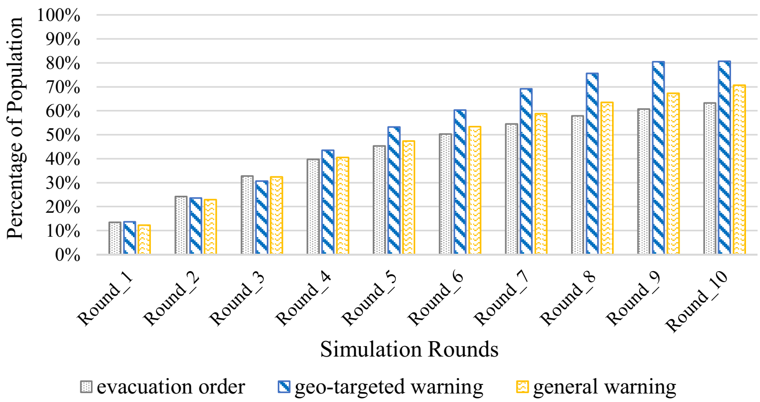


**Fig. 9** The percentage of the population who decide to evacuate under three warning scenarios over time

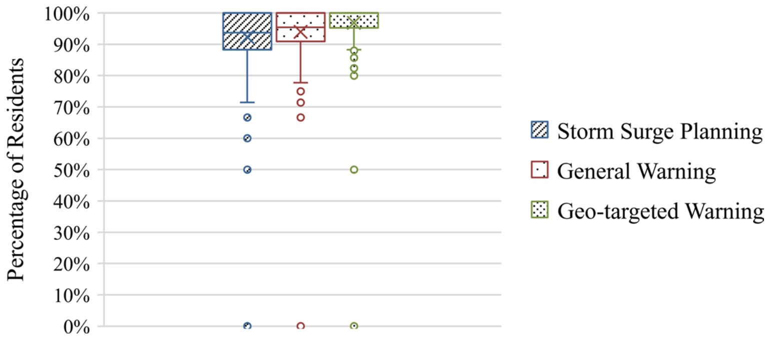


**Fig. 10** The distributions of residents' percentage who decide to evacuate in high-risk regions at 9:00 A.M. EST September 4th

zones but limited evacuation routes (see Fig. 10). We found that census tracts of higher risks had a higher percentage of the population who decided to evacuate than results under the geo-targeted warning than in the comparison scenarios. This means geo-targeted warnings contain more specific risk information of the hurricane for census tracts. The potential reason for the difference in the outcomes is related to the distinct warning messages. Geo-targeted warning messages tended to reflect the actual hurricane risks in the local census tract and helped agents to form an accurate perception of the hurricane risks, which was the basis of an evacuation decision that was suitable for the faced hurricane risks. With geo-targeted warning messages, agents who lived in the high-risk regions were more likely to perceive the actual hurricane risk and more likely to decide to evacuate. In the contrast, because of insufficient consideration of environmental conditions (specially built environment, such as land use), general warnings and storm surge planning did not reflect the local hurricane risk faced by the agents in the surrounding built environment, and agents were not likely to make the evacuation decision.

Such warnings may increase residents' perception of the hurricane's potential negative impacts and motivate them to evacuate, and they can better motivate the high-risk population to evacuate.

## 6 Discussion

This research addresses several knowledge gaps in the current literature body, including (i) the lack of integrated methods for geo-defining fine-grained warning zones (most previous works focused on the geo-delivery process) (Wood 2018); (ii) focusing on evacuation transportation but neglecting or simplifying the decision-making process when simulating residents' evacuation behaviors (e.g., Ukkusuri et al. 2017; Zhu et al. 2018); and (iii) the lack of studies that have modeled effects of geo-targeted warnings on evacuation decisions. Specifically, current warning systems of hurricanes (e.g., WEA) distribute warning messages at the county level, even though the risk levels faced by individual residents within a single county vary greatly. To address the limitation, this research refines the scale of geo-defines warning zones to the census tract level, and the warning messages can accurately deliver specific risks for the finer-spatial areas. To address the research gap of the simplified decision-making process of residents in response to warnings, we used BDI theory and the outcomes of previous empirical studies (e.g., Huang et al. 2016; Hasan et al. 2011) to simulate residents' evacuation decisions based on their socio-demographic characteristics and the warning messages they received. Also, very little research has investigated the effect of geo-targeted warnings in motivating evacuation (Wood 2018). To the best of our knowledge, we are among the first to investigate the effects of geo-targeted warnings and compare the outcomes with other types of warning messages (i.e., general warnings, and warnings based on storm-surge planning). Our simulation outcomes revealed that the geo-targeted warnings can motivate evacuation in high-risk areas: by considering environmental aspects of the disaster-affected areas, we can establish finer-scale geo-warning zones, which provides bases for geo-targeted warnings that motivate more residents to evacuate before a severe hurricane.

There are a few limitations related to data availability and model assumptions. Future work can address them in different directions. First, some personal factors that may impact individuals' decision makings were assumed as the same or not fully considered in our BDI-based decision-making models, such as personal hurricane experience and psychological status. BDI and DFT have also been criticized for generating heterogeneous decisions and inter-agent differences (Adam and Gaudou 2016). However, our selected methods are still effective in simulating aggregated individual decisions for the studied population. We also assumed that the agents made decisions independently and did not consider the social network's influences due to limited available data. Future research can focus on specific communities (e.g., physical neighborhoods and social network platforms) and consider more personal features (e.g., psychological factors) in the decision-making process. Second, the research is also limited by the spatial and temporal units of available datasets. For example, hurricane records from NOAA include attributes of each hurricane for the whole affected region, so we can only speculate about its attributes and risk at the census tract level. The coarse-grained data of hurricane records may lead to low accuracy in the geo-defining of warning zones. Also, we can only obtain the hurricane records every six hours, it is difficult to simulate residents' decision-making processes over smaller consecutive time windows (e.g., one hour or 30 min). With the improvements of hurricane project technologies, future studies can study the effects of different warning strategies with finer-grained datasets. Third, future research can employ high-resolution human mobility data (e.g.,) collected from individuals' mobile devices to investigate the real-time mobility changes after receiving any warnings before hurricanes. We did not find any open-access data which recorded people's evacuation decisions about Hurricane Dorian in Miami-Dade County, so we were not able to compare simulation outcomes with the real-world scenario. However, we have compared the simulation outcomes of geo-targeted warnings with the two other scenarios, which approximated the major real-world warning dissemination approaches. With more available individual-level decision making and evacuation data, future work can compare evacuation decisions across scenarios and keep refining models with new warning strategies.

## 7 Conclusion

This interdisciplinary research explores how environmental aspects of disaster-affected areas are considered in warning messages, and to what extent geo-targeted warnings at fine spatial scales can motivate high-risk residents to evacuate. It finds that geo-targeted warnings, which consider the fine-scaled data of the local built environment in the geo-defining process, can motivate high-risk residents to evacuate in simulated warning scenarios before a hurricane. The research contributes to the current knowledge body on understanding the effects of geo-targeted warning on evacuation decision making and the differences between general warning messages and geo-targeted warnings. It advances the current geo-defining process by considering the local risks of residents and including such information into warning messages. This research also highlights the importance of providing accurate messages during weather risk communication. The research methodology can also be used to study geo-targeted warnings for other extreme events such as wildfire, severe winter storms, and tornados. Florida expects impacts of the Atlantic hurricane season from June to November every year. It is urgent and time-critical that we understand the influences of different warning strategies on people's evacuation decisions. These research outcomes can inform local National Weather Service forecast offices and disaster responders regarding how to geo-define warning zones and design targeted warning messages based on multi-sourced hazards and the built environment data, and understand which warning strategy is more effective in terms of motivating evacuations over time. More effective risk communication and warnings can save more lives and mitigate damages caused by hurricanes, the storm surge, and following flooding. The more targeted warning can also motivate residents to take necessary hazard prevention actions and to evacuate if necessary.

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**Author contributions** Shangde Gao and Yan Wang were responsible for conceptualization and methodology. Shangde Gao performed data curation, formal analysis, validation, writing—original draft and visualization. Yan Wang performed writing—review & editing, supervision, project administration, funding acquisition.

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**Availability of data and material** All the data used in this research (e.g., hurricane data, land use data and census tract data) are public-accessible, which can be downloaded based on the websites in the reference list. The simulation outcomes are listed as maps in the supplementary material.

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